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ORIGINAL ARTICLE

Forecasting China-Africa economic integration using Wavelet-ARIMA hybrid approach

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ABSTRACT

China-Africa economic integration generally looks lucid, as evidenced by rising bilateral trade, as well as Chinese FDI, aid, and debt financing for infrastructure development in Africa. The engagement, however, appears to be strategically channeled to benefit China's resource endowment strategy. First, Chinese FDI in Africa is primarily resource-seeking, with minimum manufacturing value addition. Second, China has successfully replicated the Angola model in other resource-rich African countries, and most infrastructure loans-for-natural resources barter deals are said to be undervalued. There is also a resource-backed loan arrangement in place, in which default Chinese loans are repaid in natural resources. Third, while China claims that its financial aid is critical to Africa's growth and development processes, a significant portion of the aid is spent on non-development projects such as building parliaments and government buildings. This lend credence to the notion that China uses aid to gain diplomatic recognition from African leaders, with resource-rich and/or institutionally unstable countries being the most targeted. The preceding arguments support why Africa's exports to China dominate other China's financial flows to Africa, and consist mainly of natural resources. Accordingly, this study aims to forecast China-Africa economic integration through the lens of China's demand for natural resources and Africa's demand for capital, both of which are reflected in Africa's exports to China. The study used a MODWT-ARIMA hybrid forecasting technique to account for the short period of available China-Africa bilateral trade dataset (1992–2021), and found that Africa's exports to China are likely to decline from US$ 119.20 billion in 2022 to US$ 13.68 billion in 2026 on average. This finding coincides with a period in which Chinese demand for Africa's natural resources is expected to decline.

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Africa's exports to China; autoregressive integrated moving average (ARIMA); China-Africa economic integration; maximal overlap discrete wavelet transform (MODWT)

JEL CLASSIFICATION

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1. Introduction

China has shown a growing interest in trading with Africa since the 1990s and in the past two decades, it has also become increasingly involved in financing Africa through loans and Foreign Direct Investments (FDI). The obvious source of these developments is the establishment of the Forum on China-Africa Cooperation (FOCAC) in 2000, which unquestionably shifted China-Africa relations from political to economic. The economic engagement was amplified by the Belt and Road Initiative (BRI) of 2014. China is now Africa's largest trading partner and financier, having surpassed the United States (US) in 2008 and 2009, respectively.

FOCAC was established to facilitate multilateral consultations and collective engagement between China and African countries. The pact mandates its members to convene for ministerial conferences every three years since its inception to discuss progress and future endeavours. The latest (eighth) ministerial conference was held in 2021 in Senegal under the theme "Deepen China-Africa Partnership and Promote Sustainable Development to Build a China-Africa Community with a Shared Future in the New Era". These ministerial conferences are specifically intended to strengthen China-Africa economic ties, and this has been met with mixed reactions. While African governments seem pleased with the results of China-Africa economic ties, most scholars, media, and analysts have expressed concern over Africa's failure to take action against China's immoral economic practices and exploitative behaviour. BRI was launched to develop Africa's hard infrastructure, primarily transport, to facilitate South-South and North-South trade. Nevertheless, some analysts view BRI as an exploitation tool aimed at facilitating natural resource transportation to China.

As Africa's leading trading partner and financier for infrastructure projects such as transportation, energy, and communication, China has been active in Africa through trade and hard infrastructure construction. China has also been active in Africa's mining sector through resource-seeking FDI. Trade openness, mining, and infrastructure development have been consistently featured in African countries' development agendas to date, demonstrating their significance in advancing for sustainable economic growth and development. This implies that China-Africa economic integration has the potential to address some of Africa's sustainable growth and development challenges. However, China's immoral economic practices and exploitative behavior in Africa, coupled with the continent's weak governance system and inability to adopt a unified policy toward the Asian giant, have the potential to derail the growth and development opportunities that African countries are expected to reap as a result of this integration. China's immoral practices also jeopardize Africa's growth and development momentum.

More importantly, China-Africa economic integration is more pronounced through trade, with high exports of African natural resources to China and imports of Chinese finished products to Africa. The natural resources are mainly obtained through resource-seeking Chinese FDI, resource-backed loans in which defaulted Chinese loans are paid in natural resource, and undervalued infrastructure loans-for-natural resources barter deals. In this regard, "China-Africa" economic cooperation should be interpreted with caution. While the term appears to cover China's economic integration with Africa as a continent, China's financial flows to Africa in the form of Chinese loans, FDI, and aid, as well as African exports to China, are concentrated in a few resource-rich African countries. This shows that China's economic integration with Africa is not without resource-rich African countries, signifying its strategic engagement for resource endowment. It should also be noted that, whereas the recipients of Chinese finances in Africa are few resources-rich countries, China's exports to Africa are fairly spread across the continent, indicating its market-seeking motive.

The above discussions indicate that Africa's exports to China are a close proxy for China-Africa economic integration, taking into account both China's demand for natural resources and Africa's demand for capital. Forecasting Africa's exports to China is thus necessary to inform counter-policies that could ensure a win-win outcome. This topic has received little attention due to a lack of reliable and consistent data on China-Africa bilateral financial flows. Consistent data on African exports to China are currently available on the China Africa Research Initiative (CARI) database from 1992 to 2021. This time dimension, however, is too short for forecasting using classical techniques such as Autoregressive Integrated Moving Average (ARIMA). The current study covers this methodological gap using the Wavelet-ARIMA hybrid forecasting technique. The forecasted trend is required to inform counter-policies that could ensure a win-win outcome from China-Africa economic integration, which include, among other things, African governments reforming governance frameworks to combat China's exploitative behaviour and immoral economic practices.

The rest of this paper is organised as follows: Section 2 discusses stylized facts about China-Africa economic integration and the theoretical underpinnings of the study. The specifications of ARIMA and MODWT modelling techniques as well as the implementation of the MODWT-ARIMA hybrid approach are defined in Section 3 while the results are presented and discussed in Section 4. The study is concluded in Section 5.

2. Stylized facts and theoretical underpinnings

Figure 1 shows that China-Africa economic engagement favours China's Global South, with more China's exports to Africa than Africa's exports to China. Moreover, the financing consists more of loans than investments (FDI). This is cause for concern because it reflects financial outflow from Africa to China. According to Pigato and Tang (2015), Africa has become a home for low-quality Chinese products, while Chinese FDI is earmarked to exploit natural resources in Africa. Other methods used by the Chinese to siphon Africa's resources include resource-backed loans and infrastructure loans-for-natural resources barter deals. These arrangements are common in Angola under the "Angola Model" (Begu et al., 2018; Haifang, 2017; Jureńczyk, 2020; Machado, 2021), which China appears to have successfully implemented in other resource-rich African countries such as Congo, DRC, Equatorial Guinea, Nigeria, Sudan, South Africa, Zambia, and Zimbabwe; hence, a large portion of Chinese loans to African countries is provisioned for mining and infrastructure development (Ngundu, 2022; Ngundu and Ngalawa, 2023). The aforementioned narratives explain why Africa's exports to China are rich in natural resources.

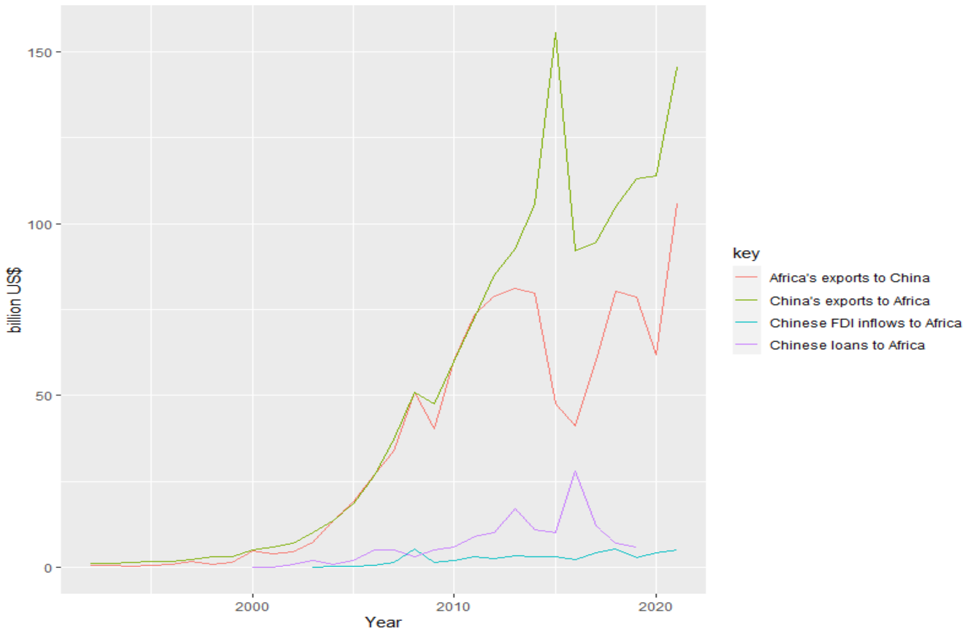

Figure 1. China-Africa financial flows.
Source: *Authors' computation using CARI dataset (CARI, 2021).*

There are also geopolitical implications, such as China trapping African countries in unsustainable loans to achieve its geopolitical agenda. This is evident in Zambia (during the presidency of President Edgar Lungu) and Kenya (during the presidency of President Uhuru Kenyatta), where media reports emerged in 2020/2021 claiming that the Chinese had captured state assets in exchange for their defaulted loans. Furthermore, Chinese hackers were recently reported to have been spying on Kenyan key government ministries since 2019 in order to obtain information about Chinese loans, Kenyan foreign acquired loans, and the country's repayment strategies. Although China dismissed the allegations as "far-fetched and sheer nonsense", this could be a warning to African countries to be cautious given China's geopolitical agenda narrative. In any case, China would never have admitted to such immorality. Such revelations are evidence of mistrust and panic, indicating that China has scrambled to dominate Africa without exercising due diligence (concessional) or with a hidden debt trap agenda.

Another perplexing issue is that the majority of Chinese debt financed infrastructure development projects are executed by Chinese contractors with little participation from domestic firms and labour. As a result, in addition to repayments, Chinese loans in Africa generate project contracts and employment for them at the expense of the African governments. Only the African and Chinese governments know whether this is part of the loan's contractual terms or if China is simply taking advantage of the continent's poor governance structures. In general, all China-Africa economic deals, particularly Chinese loans have been subjected to scrutiny due to transparency issues. To the best of our knowledge, no loan repayment track records are available in the public domain, nor are loan terms disclosed.

The lack of disaggregated trade data on China-Africa bilateral trade in finished goods and intermediates makes it difficult to understand what China's exports to Africa consist of. China's exports to Africa should be ideally higher in intermediates than finished goods. Higher exports of Chinese intermediates to Africa reflect Africa's participation in global value chains (GVC) via backward linkages, which is an essential component for manufacturing output growth, job creation, and knowledge and technology spillovers. Higher exports of finished goods to Africa, on the other hand, displace domestic products, killing domestic industries and having a severe impact on small and medium-sized enterprises (SMEs). As noted above, some researchers argue that China's exports to Africa are predominantly low-quality finished products. Furthermore, an analysis conducted using the CARI dataset on China-Africa bilateral trade flows shows that, unlike Africa's exports to China, as well as Chinese FDI and loans, which are concentrated in a few resource-rich African countries, China's exports to Africa are fairly distributed across the African continent (CARI, 2021). To this end, data seem to support the prevailing narratives that China is increasingly engaging African countries with market-seeking and resource-exploitation motives, taking advantage of the continent's weak institutional framework.

This study focuses on African exports to China for two reasons. First, they are thought to represent the value of Africa's wealth that the Chinese are exploiting. Second, they can be used to quantify the China-Africa economic integration, taking into account China's demand for natural resources and Africa's demand for capital. Trade flows, generally, are considered important economic integration indicators between economies (Arribas et al., 2007) and international economic integration is vital for the growth and development of developing economies such as Africa because it facilitates the transfer of physical capital, technology, and knowledge (Abesadze, 2017; Schiere, 2011). As a result, the accurate forecasting of trade flows evolution as an economic integration indicator is crucial for planning and policy development purposes, which is this study's main contribution. Precisely, an attempt is made in this study to forecast Africa's economic integration with China five years ahead of 2021, using the growth rate of Africa's export to China for the period 1993–2021 as the integration indicator in the modern non-parametric technique, the wavelet-ARIMA hybrid forecasting technique. Following Chakraborty and Ghosh (2020), Nury et al. (2017), Nguyen and He (2015), Paul and Ghosh (2013), and Schlüter and Deuschle (2010), our strategy is to use wavelets to help enhance forecast accuracy by converting the original series into simpler time series that are more receptive to the widely considered classical forecasting technique, the ARIMA modelling.

In recent years, wavelet transformation-based forecasting has been widely recommended over classical forecasting techniques, ARIMA in particular, for two major reasons. First, whereas ARIMA modelling is effective in stationary time series data only, wavelet transforms can decompose original non-stationary time series data into a linear combination of different frequencies without changing the pattern of the series (Schlüter and Deuschle, 2010). Thus, by imposing some restrictions we can measure the impact of the integration indicator's pattern with a specific frequency at a specific period. Second, the forecasting accuracy of ARIMA depends on data availability and anecdotal evidence suggests at least sixty-five (65) observations. Bilateral data on China-Africa financial flows are still limited in the public domain. Meanwhile, the bilateral dataset on Africa's export flows to China is readily available only for the 1992–2021 period (CARI, 2021), making forecasting

Africa's integration with China hardly possible using ARIMA modelling. The ARIMA's requirement to have a reasonably large sample size is adequately addressed by the redundant or time-invariant version of the Discrete Wavelet Transform (DWT), the Maximal overlap discrete wavelet transform (MODWT). According to Nguyen and He (2015), MODWT "can be applied to a time series with arbitrary length". Likewise, Paul and Ghosh (2013) note that "MODWT is well defined for all sample sizes". With these features, integrating MODWT with ARIMA modelling is anticipated to improve the forecasting accuracy of Africa's economic integration with China.

3. ARIMA and Wavelet-ARIMA hybrid approach

3.1. ARIMA

In non-seasonal stationary time series data, ARIMA consists of three elements namely, the autoregressive term (AR), the differencing term (I) and the moving average term (MA) (Hyndman and Athanasopoulos, 2018). Respectively, the subscripts p, d, and q are widely used as a proxy for ARIMA elements, where p is the number of past observations used for predicting the next value, d is the number of times the differencing operation is performed to make the univariate series stationary, and q is the number of past forecast errors used to forecast the future values. Thus, the ARIMA (p, d, q) model can be specified as:

$$x_t' = \alpha + \phi_1 x_{t-1}' + \dots + \phi_p x_{t-p}' - \theta_1 \varepsilon_{t-1} - \dots - \theta_q \varepsilon_{t-q} + \varepsilon_t \tag{1}$$

where x' is the differenced univariate series at time t, α is the mean, and ε represents white noise. The subscripts ϕ and θ denote AR, and MA parameters, respectively.

To implement ARIMA (p, d, q) model, two steps are necessary in their order. The first step is to ensure that the stationarity condition is met by determining the lowest value[1] of that can make the univariate time series stationary. Therefore, depending on the series, x'_t can be differenced more than once to make it stationary. The second step is to determine the value of p and q required by the model to rectify autocorrelation in x'_t using the Partial Autocorrelation (PACF), and the Auto-Correlation Function (ACF) plots, respectively. Accuracy metrics mainly the Mean Absolute Percentage Error (MAPE) and the Root Mean Squared Error (RMSE) are used to check the performance of the model. For comparison purposes, these accuracy metrics are utilised together with Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to determine the best-fitted forecasting model. The best ARIMA (p, d, q) model is chosen based on the least values of accuracy metrics, AIC and BIC.

3.2. MODWT

There are two types of Wavelet transforms that can be used to analyse financial and economic time series data in discrete form, orthogonal DWT and non-orthogonal MODWT (Dghais and Ismail, 2013). Both transforms are suitable for multiresolution analysis (MRA) or scale-based addictive decomposition, and variance analysis (ANOVA) or scale-based energy decomposition. However, in several studies (see, for example, Nguyen and He, 2015; Nury et al., 2017; Paul and

1. Over-differencing may affect the coefficients (ϕ and θ) of the model.

Ghosh, 2013), a comparison between these wavelet transforms shows that MODWT performs better than DWT in time series forecasting. MODWT is considered a modification of DWT due to various reasons. First, it is time-invariant. Second, it can be applied to sample sizes of any length, unlike the dyadic DWT which requires the sample size N to be multiple of a power of two (2^j) where the number of scales or decomposition levels j runs from 0 to J ($j = 0, \ldots, J$). Third, it uses down-sampled values removed by DWT at each decomposition level. Fourth, the scaling and detail coefficients generated using MODWT are coherent with the original time series because it does not shift the original series' peak as DWT does. Fifth, MODWT MRA's scaling and detail coefficients are associated with zero phase filters, resulting in a more asymptotically efficient wavelet variance estimator than DWT.

3.3. Econometric specification of MODWT

As noted above, the MODWT is an improved version of the DWT, implying that its specification is deduced from the DWT. Wavelet transforms, in general, consist of the father wavelet function (ϕ) which integrates to one (1) and the mother wavelet function (ψ) which integrates to zero (0). Both functions decompose signals at different timescales. The function ϕ captures the smooth and low-frequency signal components (scaling or approximation or smooth coefficients) whereas ψ captures the detail and high-frequency signal components (detail or wavelet coefficients). Given α as the scale parameter and b as the translation or shift parameter, the father and the mother wavelet functions can be specified as shown in Equations (2) and (3), respectively (Rhif et al., 2019).

$$\phi_{a,b}(t) = \frac{1}{\sqrt{a}}\phi\left(\frac{t-b}{a}\right) \tag{2}$$

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{3}$$

Since DWT applies a dyadic grid, $\alpha = 2^j$ and an integer $b = k2^j$ where the shift or translation index $k = 1,\ldots, 2^{-j}N$. Thus, in the case of DWT, Equations (2) and (3) can respectively be deduced as follows:

$$\phi_{j,k}(t) = 2^{-j/2}\phi(2^{-j}t - k) \tag{4}$$

$$\psi_{j,k}(t) = 2^{-j/2}\psi(2^{-j}t - k) \tag{5}$$

A DWT decomposition yields two vectors: detail coefficients for high frequencies and scaling coefficients for low frequencies (trend) (Dghais and Ismail, 2013). At level 1, D_1 and S_1 represent the detail and scaling coefficients, respectively. The scaling coefficients (S_1) are decomposed further to D_2 and S_2. From the trend series S_2, the decomposition process continues such that the J-level decomposition crystal or the number of coefficients in the specified components can be represented as S_J, D_J, D_{J-1}, D_{J-2}, ..., D_1. Thus, the approximation of the wavelet series to a discrete signal $x(t)$ can be expressed as:

$$x(t) = \sum_k S_{j,k}\phi_{j,k}(t) + \sum_k d_{j.k}\psi_{j,k}(t) + \cdots + \sum_k d_{1,k}\psi_{1,k} \tag{6}$$

where the scaling coefficient ($S_{j,k}$) and the detail coefficients $d_{j,k}$, ..., $d_{1,k}$ are predicted as follows:

$$S_{j,k} \approx \int \phi_{j,t}(t)x(t)dt \tag{7}$$

$$d_{j,k} \approx \int \psi_{j,t}(t)x(t)dt \tag{8}$$

As is true with DWT, MODWT can similarly apply low and high-pass filters to the input signal at each level. However, the MODWT is an undecimated transform, which means that the number of scaling and detail coefficients generated has the same cardinality as the original data at every transform level, making ARIMA modelling more robust (Gurumoorthy et al., 2020; Joo and Kim, 2015; Nguyen and He, 2015; Paul and Ghosh, 2013).

To implement MODWT, DWT filters ($S_{j,k}$ and $d_{j,k}$) must be renormalised by multiplying each filter with $2^{\frac{-j}{2}}$ to remove the dyadic element. Thus, the MODWT generates the detail coefficients at each level as:

$$x_j(t) = \sum_{k=1}^{N-1} d_{j,k} 2^{\frac{-j}{2}} \psi(2^{-j}t - k) \tag{9}$$

while the scaling coefficients are generated at the final level as:

$$x(t) = \sum_{k=0}^{N-1} S_{j,k}\, 2^{\frac{-J}{2}} \phi(2^{-J}t - k) + \sum_{j=1}^{J} x_j(t) \tag{10}$$

As mentioned above, the number of decomposition levels runs from 0 to J ($j = 0, ..., J$). For any given J, MODWT generates $N(J + 1)$ coefficients (N scaling coefficients and NJ detail coefficients) while DWT returns N detail coefficients only. Furthermore, MODWT of level J is well-defined for any N, whereas DWT requires N to be an integer multiple of 2^J. In terms of scale-based energy decomposition, the MODWT divides energy across various scales and scaling coefficients as follows:

$$\|x\|^2 = \sum_{j=1}^{J} \|w_j\|^2 + \|v_J\|^2 \tag{11}$$

where w_j and v_J proxy for detail coefficients at scale j and the final level scaling coefficients, respectively.

In practical analysis, MODWT supports various wavelets including Harr, Daubechies, Biorthogonal, Symlet, Meyer and Coiflets. However, the application of Haar is deemed effective relative to other wavelets (Gurumoorthy et al., 2020; Paul and Ghosh, 2013). It is argued that Haar makes use of previous values as well as the present value, whereas other wavelets make use of subsequent values in a series. This feature makes Haar more suitable for forecasting because it does not require estimated values beyond the end of the original series, as other wavelets do by reflecting the original series, considering it as periodic, and using values from the beginning. Equations (12) and (13) respectively present the Haar wavelet's father and mother wavelet functions.

$$\phi(x) = \begin{Bmatrix} 1 & 0 \le x \le 1 \\ 0 & otherwise \end{Bmatrix} \tag{12}$$

$$\psi(x) = \begin{Bmatrix} 1 & 0 \le x \le 0.5 \\ -1 & 0.5 \le x \le 1 \\ 0 & otherwise \end{Bmatrix} \tag{13}$$

3.4. Implementation of MODWT-ARIMA hybrid approach

This study uses the growth rate of Africa's exports to China for the period 1993–2021 as an indicator of Africa's economic integration with China and the MODWT-ARIMA hybrid forecasting approach to predict the evolution of this integration five years ahead of 2021. To implement a MODWT-ARIMA hybrid technique, this study uses the "*fittestWavelet*" function in R's "*TSPred*" statistical package (Conejo et al., 2005; Joo and Kim, 2015). The function automatically applies MODWT with various automatic wavelet or filtering options to decompose the integration indicator into scaling and detail coefficients and constructs a separate model for each part. As indicated above, this study uses the Haar wavelet. The decomposed series' components are utilised as a base for forecasting and returning the next consecutive values of the integration indicator, which is likewise done using automatically fitted forecasting models. This study fits ARIMA modelling.

4. Estimated results and discussions

This section reports and discusses the findings of the study. First, we analyse the performance of ARIMA modelling alone before integrating the forecasting technique with MODWT. In ARIMA modelling, identifying the appropriate values for p, d, and q can be complicated, and the wrong selection of these parameters can lead to biased estimations (see Section 2.1). We, thus, use the "*auto.arima*" function in R's "*forecast*" estimation package (Hyndman and Khandakar, 2008). This function does the selection of p, d, and q automatically. Finally, we compare the robustness of the ARIMA and MODWT-ARIMA approaches using accuracy metrics (MAPE and RMSE), AIC and BIC.

4.1. ARIMA modelling results

Figure 2 indicates that the best ARIMA (p, d, q) model selected using the "*auto.arima*" function is the ARIMA (0, 0, 0) model with a mean of 31.47%. This is a white noise non-seasonal ARIMA model (Hyndman and Athanasopoulos, 2018), which implies that the integration indicator had no clear trend in the 1993–2021 period and, therefore, cannot be predicted.

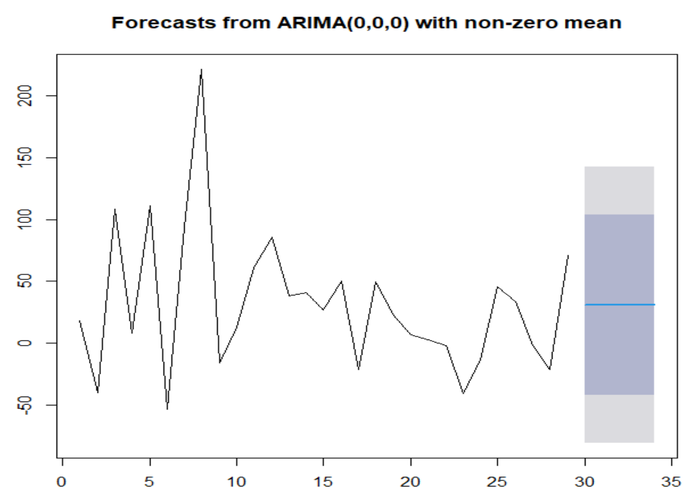

Figure 2. ARIMA modelling results.
Source: Authors' estimation using the "auto.arima" function in R's "forecast" estimation package.

4.2. MODWT-ARIMA hybrid approach results

For the computation of MODWT and forecasting of Africa's economic integration with China using the MODWT-ARIMA approach, the empirical strategy and implementation procedure discussed in the preceding section are followed. According to **Figure 3**, the number of decomposition levels J is 2 (W_1 and W_2). We chose the Haar wavelet for filtering the integration indicator on a scale-by-scale basis to deduce its pattern or trend. The subscript x denotes the original plot of the integration indicator, W_1 and W_2 represent detailed MODWT components, and V_2 is the trend of the smoothed MODWT coefficients.

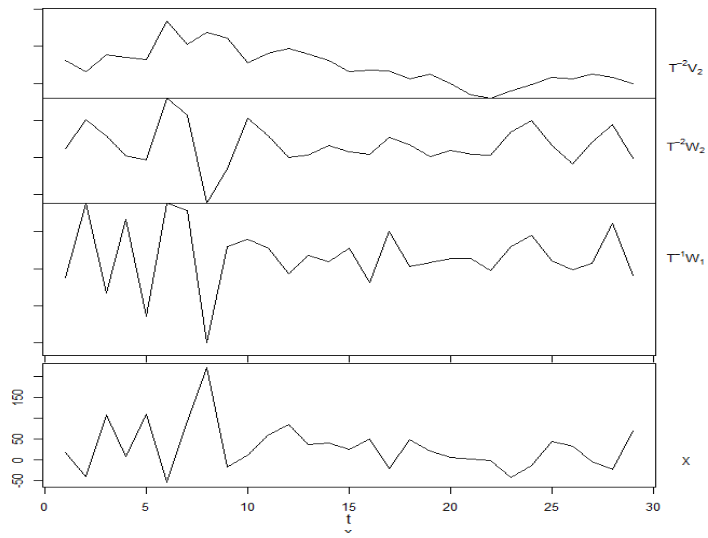

Figure 3. MODWT of Africa's exports to China (export growth rate) from 1993 to 2021.
Source: Authors' computation using R.

Apart from the fact that our sample size is small (29 observations from 1993 to 2021), the smoothed trend in **Figure 3** shows a non-linear trend of the integration indicator, rendering ARIMA ineffective in forecasting Africa's economic integration with China, and thus the results in **Figure 2** are not surprising. Specifically, the integration indicator exhibits seasonality features.

Next, we present forecasted integration indicator values five (5) years ahead of 2021 (see **Table 1** and **Figures 4** and **5**). **Table 1** summarizes the projected amounts and growth rates of African exports to China between 2022 and 2026. **Figure 4** exhibits the forecasted growth rates of Africa's exports to China while **Figure 5** depicts the respective export flows[2] which we calculated based on the predictions in **Figure 4**.

Africa's exports to China are expected to decline from US$ 119.20 billion in 2022 to US$ 13.68 billion in 2026 on average, with a lower and upper bound of US$ 77.63 billion and US$ 160.76 in 2022 and US$ 6.77 and US$ 20.60 in 2026, respectively. According to the General Administration of Customs of the People's Republic of China, China's imports from Africa totalled US$ 117.51 billion in 2022. This value falls within our forecast range and is not significantly different from the forecasted mean value of US$ 119.20 billion.

2. $Export\ Flows_t = Export\ Flows_{t\text{-}1}\left(\frac{Export\ growth(\%)_t}{100} + 1\right)$

Table 1: Summary of the Wavelet-ARIMA Hybrid forecasted values.

Year	Africa's exports to China (billion US$)			Annual percentage change of Africa's exports to China (%)		
	Lower bound	Mean	Upper bound	Lower bound	Mean	Upper bound
2022	77.63	119.20	160.76	–26.60	12.71	52.01
2023	37.68	87.30	136.92	–51.46	12.45	76.37
2024	17.73	41.99	66.25	–52.94	11.44	75.82
2025	9.25	20.50	31.76	–47.86	15.62	79.09
2026	6.77	13.68	20.60	–26.80	48.00	122.79

Source: Authors' computation using output from the "fittestWavelet" function in R's "TSPred" statistical package.

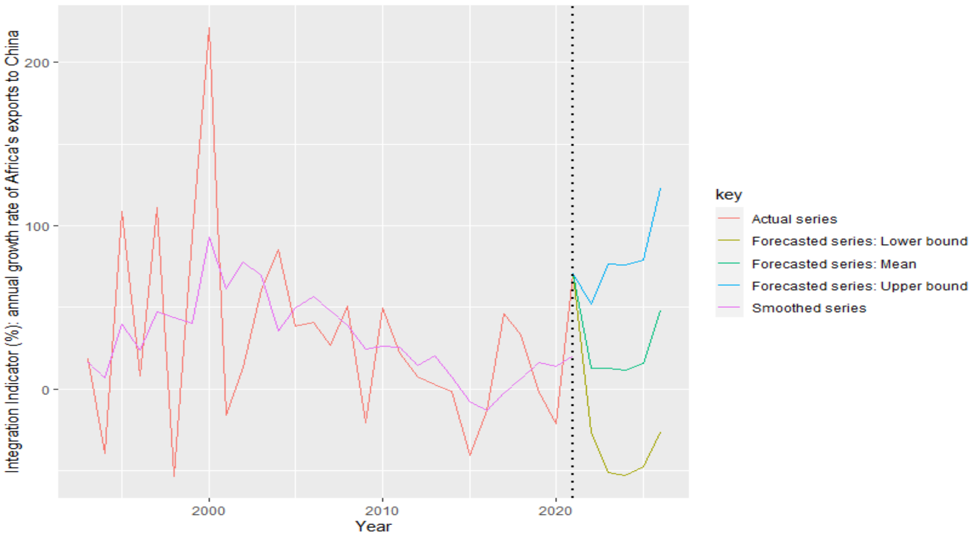

Figure 4. MODWT-ARIMA hybrid forecasted series.
Source: Authors' computation using output from the "fittestWavelet" function in R's "TSPred" statistical package.

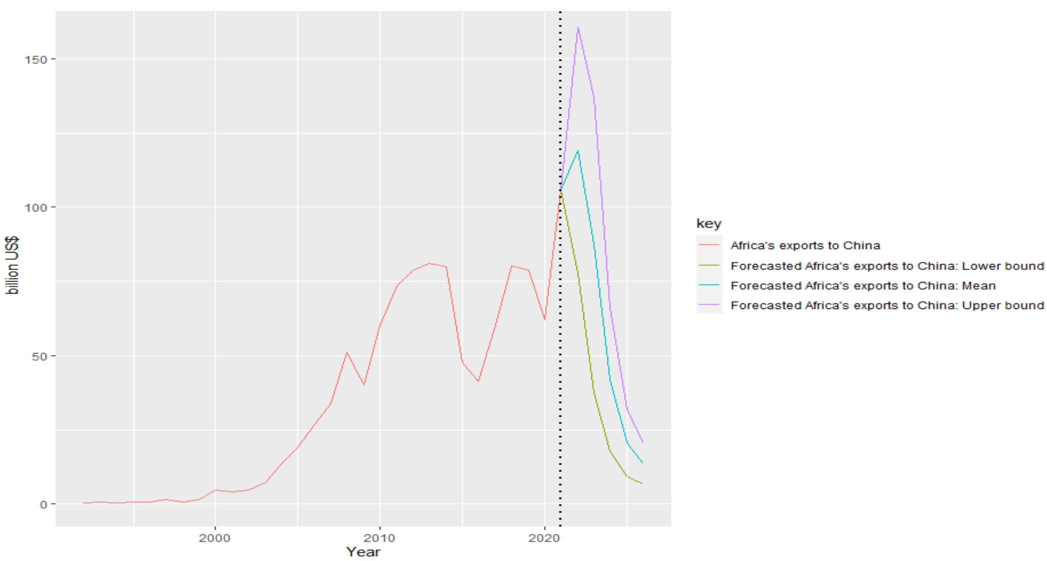

Figure 5. Forecasted Africa's exports to China.
Source: Authors' computation based on the MODWT-ARIMA hybrid output and CARI dataset.

Figures 3 and **4** show that the period 2022–2026 represents another downward episode in the seasonality trend of African exports to China, following an upward episode in the period 2015–2021.

The black dotted line in **Figures 4** and **5** splits forecasted values from actual values, with 2021 marking the end of actual values.

The discussion that follows looks at what drives Africa's exports to China, which appear to follow a seasonality pattern of about 5 years long downward and upward episodes.

4.3. Discussion of the findings

In the 1992–2019 period, 84% of Africa's exports to China were sourced from ten (10) resource-rich countries, with 36% concentrated in Angola (see **Figure 6**). As highlighted in various studies (see, for example, Begu et al., 2018; Haifang, 2017; Jureńczyk, 2020; Machado, 2021; Prabhakar et al., 2020), this indicates that Africa's export volumes to China are dominated by natural resources, driven by China's increasing demand for raw materials to supply its booming manufacturing industry. It is noted that Africa's exports to China are mainly sourced from resource-seeking Chinese investments in Africa (Begu et al., 2018), natural resources backed Chinese loans in which default repayments are made through the extraction of natural resources (Were, 2018), and infrastructure loans-for-natural resources barter deals (Cissé, 2013). Thus, the seasonality feature in African exports to China, depicted in **Figures 4** and **5**, is ideally subject to the Chinese appetite for natural resources.

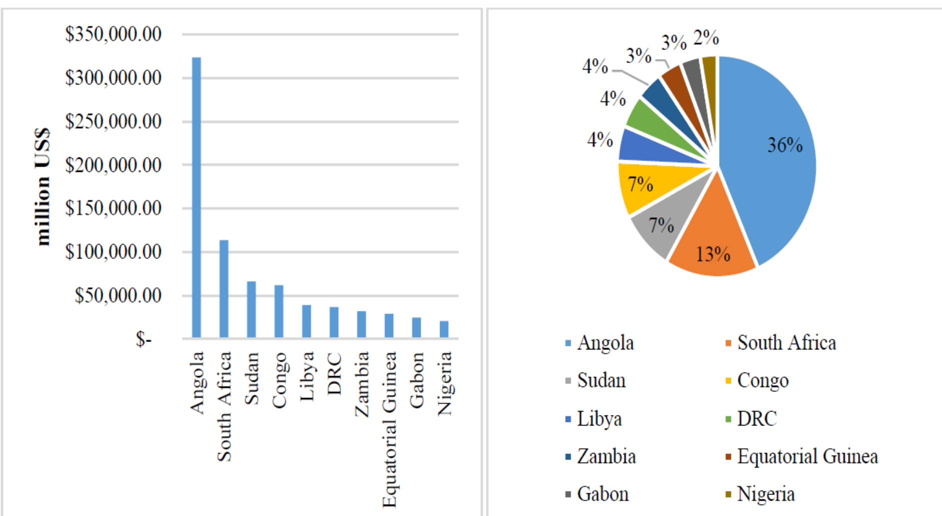

Figure 6. The distribution of Africa's exports to China for the period (1992–2019).
Source: Authors' compilation using the CARI dataset (CARI, 2021).

The projected decrease in African exports to China corresponds to what Sun (2021) described as a "shift away from infrastructure" demonstrated at the 8th FOCAC 2021 ministerial meeting. As previously stated, Chinese debt financing for infrastructure development has been one of the primary strategies used by the Chinese to siphon Africa's natural resources, and shifting away from it implies a considerable decline in Africa's exports to China. Unless Chinese finds another source of raw materials, which is unlikely given the exploitation convenience that they enjoy in Africa, the strategy is likely to resurface with an increase in demand for natural resources to supply Chinese factories, resulting in another upward swing of African exports to China.

However, there is room for improvement in both export values and decisive outcomes if the China-Africa natural resources exchange deals can be properly valued in line with global market commodities' prices and if Africa improves its participation in this integration. Meanwhile, most China-Africa natural resources exchange deals are undervalued relative to the global market prices (Cissé, 2013). Moreover, Africa has remained reluctant towards China's exploitative attitude (Jureńczyk, 2020; Schiere, 2011).

4.4. Robustness checks

The results to evaluate fitness and prediction accuracy between ARIMA and MODWT-ARIMA hybrid forecasting techniques are given in **Table 2** below.

The results in **Table 2** indicate that the accuracy metrics, AIC and BIC estimates of the MODWT-ARIMA hybrid model are less than that of ARIMA modelling, which implies that the latter model is the best-fitted forecasting technique for our data.

Table 2. Robustness checks.

ARIMA				MODWT-ARIMA Hybrid Approach			
MAPE	**RMSE**	**AIC**	**BIC**	**MAPE**	**RMSE**[3]	**AIC**	**BIC**
283.54	56.43	298.41	301	121.41	34.6	225.28	226.54

Source: Authors' computation based on the "auto.arima" (ARIMA) and 'fittestWavelet" (MODWT-ARIMA) functions.

5. Conclusion

Forecasting of time series data forms a crucial research area in economics because it informs economic decisions and policy development. Most of the time series data in economics are non-linear, chaotic and scarce, which makes forecasting using classical techniques hardly possible. In this study, we use CARI's dataset on Africa's export flows to China as an indicator of Africa's economic integration with China for the 1993–2021 period, to show that one can counteract the linearity, stationarity and sample size conditions of classical forecasting techniques by integrating the techniques with wavelet analysis. The forecasting accuracy also improves significantly through this hybridisation. As expected, implementing ARIMA modelling directly on the data indicated that the integration indicator is white noise and hence cannot be predicted. However, the MODWT-ARIMA hybrid model estimates show that Africa's economic integration with China mimics a seasonal pattern of roughly medium-term long downward and upward episodes, with the projected period falling in the downward episode. Precisely, Africa's exports to China are expected to decline from US$ 119.20 billion in 2022 to US$ 13.68 billion in 2026 on average, with a lower and upper bound of US$ 77.63 billion and US$ 160.76 in 2022 and US$ 6.77 and US$ 20.60 in 2026, respectively. This finding appears to reflect China's shift away from infrastructure development projects in Africa, as depicted in the Forum on China-Africa Cooperation (FOCAC) 2021 ministerial

3. The *"fittestWavelet"* function produces MSE among other prediction accuracy metrics. RMSE was therefore calculated manually as $\sqrt{MSE}$.

conference. Chinese debt financing for Africa's infrastructure development has been one of China's primary strategies for siphoning Africa's natural resources, and shifting away from it implies a significant decline in Africa's exports to China. Be that as it may, Africa remains a significant source of natural resources not only for China but also for the global north. Thus, this can be win-win economic integration if African countries improve their bargaining position and institutions involved in the trade and other financial arrangements with China. On the other side, China must be morally responsible to its African partners.

Author contributions

Conceptualisation, MN; methodology, MN; validation, MN; formal analysis, MN; investigation, MN; resources, RM; writing the original manuscript, All authors; writing-reviewing and editing, RM. All authors have read and agreed to the published version of the manuscript.

Conflicts of interest

The authors declare no conflict of interest.

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